Design of Fingerprinting Technique For Indoor Localization Using AM Radio Signals

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As GPS cannot reliably reach and cover any covered area or indoor location, many past studies and research considered the application of Signals of Opportunity (SoOp) such as Wi-Fi, Bluetooth, RFID, Cellular Networks, and FM signals for indoor positioning and object tracking. However, not all SoOp can be part of the indoor positioning experiment due to some limitations; for example, not all signals are cost-effective; some are less accurate in finding position; some require additional hardware for deployment. In this study, a new technique of indoor navigation is introduced exploiting AM radio signals and the received signal strength (RSS) fingerprinting method. This research investigates the fingerprinting technique with the deterministic approach via three algorithms such as Nearest Neighbour (NN), K-Nearest Neighbour (KNN), and K-Weighted Nearest Neighbour (KWNN) for measuring the mean distance error (MDE) as the prime indicator of localization accuracy. The result demonstrates that the Nearest Neighbour algorithm performed best for K=1 and the lowest mean distance error in the ground and the first floor is less than 3m.

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ABSTRACT

As GPS cannot reliably reach and cover any covered area or indoor location, many past studies and research considered the application of Signals of Opportunity (SoOp) such as Wi-Fi, Bluetooth, RFID, Cellular Networks, and FM signals for indoor positioning and object tracking. However, not all SoOp can be part of the indoor positioning experiment due to some limitations; for example, not all signals are cost-effective; some are less accurate in finding position; some require additional hardware for deployment. In this study, a new technique of indoor navigation is introduced exploiting AM radio signals and the received signal strength (RSS) fingerprinting method. This research investigates the fingerprinting technique with the deterministic approach via three algorithms such as Nearest Neighbour (NN), K-Nearest Neighbour (KNN), and K-Weighted Nearest Neighbour (KWNN) for measuring the mean distance error (MDE) as the prime indicator of localization accuracy. The result demonstrates that the Nearest Neighbour algorithm performed best for K=1 and the lowest mean distance error in the ground and the first floor is less than 3m.

To my beloved mother Mahmuda

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Glossary of Symbols

Acronyms

3D	3 Dimensional.
AM	Amplitude Modulation
AOA	Angle of Arrival
AP	Access Point
CDF	Cumulative Distribution Function
DVB	Digital Video Broadcasting
FFT	Fast Fourier Transform
FM	Frequency Modulation
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning System
GSM	Global System for Mobile
KNN	K-Nearest Neighbour
KWNN	K-Weighted Nearest Neighbour
LBS	Location-based Services.
MDE	Mean Distance Error
NLOS	Non-Line of Sight
NN	Nearest Neighbour

RF	Radio Frequency
RFID	Radio Frequency Identification
RP	Reference Point
RSS	Received Signal Strength
SD	Spatial Diversity
SNR	Signal-to-Noise Ratio
SoOP	Signals of Opportunity
TDOA	Time Difference of Arrival
TOA	Time of Arrival
TP	Test Point
VD	Vector Distance
WLAN	Wireless Local Area Network

Chapter 1

Introduction

1.1 Introduction

Not all positioning technologies have the capability to operate in every environment due to some constraints and this has been the issue since the invention of position tracking. As the GPS (Global Positioning System) and GNSS (Global Navigation Satellite Systems) have precise localization capability, they are widely accepted as precise location tracking and positioning technologies in all areas [1]. Still, GPS and GNSS fail in specific locations, especially covered areas such as tunnels, inside buildings, urban canyons, caves, and underwater. The main reasons behind the failure of GPS and GNSS signal reception are lack of visibility of satellites and the weak RSS (Received Signal Strength) in those specific areas [2]. Popularity and demand for indoor positioning are rapidly growing for the commercial use in the field of LBS (Location- Based Services) and SNS (Social Networking Services)[3]. Examples of LBS and SNS are device tracking, military services, navigation and guidance, safety and emergency services, logistics, and product advertising [4]. To serve context-aware functionality to mobile users, Location Based Services (LBS) do not work like standard mobile services, rather LBS use mobile applications identifying a mobile user's current location. A new and enhanced level of services is delivered to the consumer based on a known location of the user. In today's world mobility matters in every aspect of life and to provide mobility services via various applications, indoor positioning through the means of LBS is becoming popular [5]. Signals of Opportunity, basically non-satellite-based RF signals, have the potential to dominate the indoor positioning field because of having the capability of RF coverage in the urban area and indoor locations where GNSS or GPS cannot reach [6]. Stronger signal reception at a low frequency make the signals of opportunity able to propagate through various barriers such as the wall, solid building structure, which is the most significant advantage of signal of opportunity [7]. Three major mediums such as radio, light, and sound are applied for signalling methods for indoor localization, for example, infrared [8], visual sensors [9], Locata [10], ultrasonic badges [11], and cricket [12]. Various research outputs showed the applications of conventional and recognized SoOPs such as Wi-Fi [6], WLAN, GSM mobile signal, Bluetooth, DVB TV signal, and FM radio signals[13] in the past. Some of the commonly used and well-known positioning techniques use Time of Arrival (TOA), Angle of Arrival (AOA), Time Difference of Arrival (TDOA), RSS (Received Signal

Strength), Data Recording, Dead Reckoning, Proximity and Scene Analysis [14]. However, past research on FM signals as a SoOp utilized for indoor navigation demonstrated that insufficient timing information and the unsynchronized signal could lead these TOA, AOA or TDOA techniques to be impractical to perform [1] whereas an RSS technique is completely free from the timing and synchronization issues. Therefore, after considering the problems related to the FM signal, our study aimed to conduct indoor localization experiments with the RSS method commonly known as fingerprinting. Signal propagation modeling can be utilized for localization; however, the signals are affected during propagation due to environmental effects such as building structure, materials, walls, barriers like glass frame and the multipath which impact the consistency of the propagation model for indoor navigation. The latest research also has demonstrated the application of multipath and NLOS for fingerprinting [5]. Some primary areas of indoor localization are still in need of improvements such as modeling of radio signal propagation and the effect of propagation on the total system [15].

On the other hand, some of these challenges, based on disadvantages for this fingerprinting technique, encouraged the author to carry on this research. According to Prashant [16], four aspects of challenges have been identified such as performance, application requirements, security, cost, and complexity.

a. Performance: Accuracy is the crucial element for location technologies, and the accuracy is indicated by distance error which is the difference between the estimated position and true or actual position. Delay, coverage, and capacity are also part of performance measurement [17].

b. Application requirements: Three main components such as granularity, accuracy and the availability of the information in a location are required to form positioning information, and are parts of application requirements, where granularity also has two types: temporal and spatial. Temporal granularity sets the speed of position information whereas spatial granularity defines the class of detail information. Based on application needs, location estimation of the positioning system is divided into two categories: a) remote-positioning which is determined by the backbone infrastructure and b) self-positioning where mobile terminal sets its position[16, 17].

c. Cost and Complexity: Deployment of localization systems involve cost and complexity which are heavily dependent on infrastructure, required extra bandwidth, reliability and fault tolerance, and the kind of technology used for positioning. Besides, deployments add the survey time and cost for installation, however, the price can be lowered by reusing the existing infrastructure of the system. Also, Prashant mentioned, when a positioning system utilized the RF fingerprinting technique, the cost, delay, accuracy and the capacity of the system are greatly influenced by the size and the location information of database [16]. The positioning system also includes the cost of power consumption at each mobile when the system is in operation [18]. Another issue has an impact on cost which is the complexity of signal processing and algorithm [17].

d. Security: The problems related to privacy are always an essential concern when positioning or tracking of an object to be determined without revealing any information to the unauthorized person or the third party. In case of reutilizing communication signals, the signals may need to be open that may cause the security breach within the positioning system. Therefore, building a security protocol within the localization network can protect unauthorized access [16]. However, due to the active nature of mobile stations and constraints of location sensing methods, reusable signals of localization system cannot be fully secured [17].

1.2 The objective of this research

Due to some gaps in recent and existing studies, this research aims to investigate utilization of signals of opportunity such as AM (Amplitude Modulation). Since the beginning of the fingerprinting technique, almost all types of (SoOp) have been used for experiments; however, this research proposes to deploy AM signals for the very first time as SoOP for localization. Some of the well-known signals of opportunity such Bluetooth, DVB TV signal, GSM mobile signal, WLAN, Wi-Fi [6] and FM radio signals [13] have already been deployed, and among these signals, Bluetooth and Wi-Fi are the most popular for high accuracy in positioning. However, due to some constraints such as the cost of resources and deployment, FM or AM signals can have potential over Wi-Fi or Bluetooth.

1.3 Contribution of this Research:

The primary aim of our experiment is to investigate the utilization of AM signal as a signal of opportunity to observe the performance, accuracy, complexity, and deployment of AM fingerprints for indoor localization. Therefore, the first contribution of this research is obtained from the significant data acquisition and analysis of AM fingerprints. To investigate the characteristics of AM fingerprints for indoor positioning, primarily the deterministic method has been used for determining the location and then we analysed the performance and the precision of AM fingerprinting using various results.

1.4 Structure of the Thesis

The structure of this dissertation is in four chapters, including two chapters which contain the main contribution of the research. The chapters are as follows

Chapter 1. Introduction

This chapter introduces the motivation and background of the research and why the study has been undertaken. Also, the section presents the summary of contribution of the research.

Chapter 2. Literature Review

This chapter includes the study of literature on various signals, indoor positioning techniques, and measurement methods. Of five parts of this chapter, the first part describes the taxonomy of indoor positioning, the second and third parts include positioning techniques and different types of signals used for navigation. The later two parts provide position estimation techniques and vector distance measurements.

Chapter 3. Design of Indoor Localization System

In this chapter, the primary model of an AM fingerprinting system and technique is examined and it is explained how the location determination was carried out using the deterministic approach. The third part of this chapter describes the experiment and data acquisition followed by result and analysis of the deterministic method.

Chapter 4. Conclusion

The outcome and contribution of the research along with the plan and recommendation for future work are presented in this chapter.

1.5 Publication from this research

Initial results of the experiment contributed to produce a conference paper.

Conference Paper:

1. M.M.Rahman, V. Moghtadaiee, and A. G. Dempster, “Design of Fingerprinting for Indoor Localization Using AM Radio Signals,”*in Proc. Of IEEE, Indoor Positioning and Indoor Navigation (IPIN), Sapporo, Japan, Sep.2017, pp.1-7*

Chapter 2

Literature Review

2.1 Introduction:

The literature review for this research provides the insight into the fingerprinting technique for indoor positioning, via presentation of coherent background for current study and drawbacks of the fingerprinting method. Basics Indoor positioning technologies; Signals used in for indoor positioning; Performance criteria for Indoor Positioning; and Methods including an algorithm for performing location fingerprinting technique are discussed [19].

2.2. Taxonomy of Indoor localization

Based on techniques, performance challenges and signals, the indoor localization system can be divided into three categories such as specialized infrastructure based, existing infrastructure based and no infrastructure based systems[20]. Based on special infrastructure and use of special hardware some of the common and popular indoor positioning are Active Badge [21], Active Bat [22], Pinpoints 3D-iD [23], Ubisense [24], PlaceLab [25], Ekahau [26], Skyhook[27].

Active Badge utilizes a small infrared (IR) badge carried by object or personnel for tracking, and the network sensors are placed within the infrastructure or the building to identify the roaming badges and reports to the server. Through the identification of badges by the particular sensor, it is possible to locate the owner's location [28]. On the other hand, Active Bat uses RF and ultrasound technologies which improve the accuracy of Active Badge. Ultra-sound receivers are organized in an array mounted on the ceiling which is all centrally connected to a server. Mobiles are considered as "Bats" and receive an RF request packet, and the ultra-sound receivers receive a reset signal from the central controller. Using multilateration algorithms the position of the Bat is determined, and the average accuracy is 2cm [28].

2.3 Indoor Positioning Techniques

Most of the latest positioning techniques can offer acceptable location estimation of the user. The methods used for position estimation are the same, and fusion of multiple methods can be used as a hybrid localization technique. Another way of performing a positioning technique is to combine all the individual outputs of estimated positions to get a final position result. However, different methods have different advantages as well as disadvantages; therefore, selection of a technique ultimately depends on the requirement and specifications of the application [29].

2.3.2 Angulation

This technique is familiar with Direction of Arrival (DOA) or Angle of Arrival (AOA) where angles are measured from the user to the transmitters. The position estimation is measured by the intersection lines set by the angles as shown in Figure 2.1. AOA or DOA can be implemented while directional antennas are used in the application [30] [31]. This technique has limitation due to multipath, NLOS and shadowing but the significant advantage of this method is no synchronization required between the user and the transmitter [32].

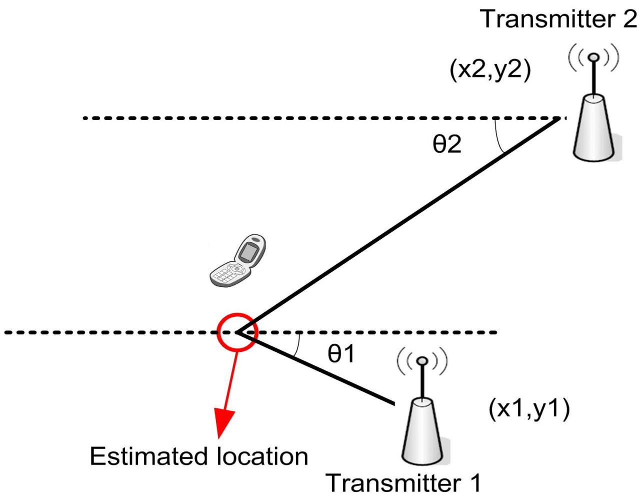

Figure 2.1: DOA/AOA as Angulation technique[29]

2.3.3 Lateration

In the lateration technique, positioning is measured using geometric circles or spheres to calculate distances between at least two known fixed transmitters with known positions and a user. Satellite communication in 3D positioning requires at least three emitters [29] . In general, four types of methods are used to measure the distance between receiver and transmitter.

• *Time Difference Of Arrival (TDOA)*, a method that measures distance based on cross-correlation between signals arriving at two stations[33]. Therefore, to a standard common time base, synchronization is essential for the code generators in each receiver (Figure 2.2) [34].

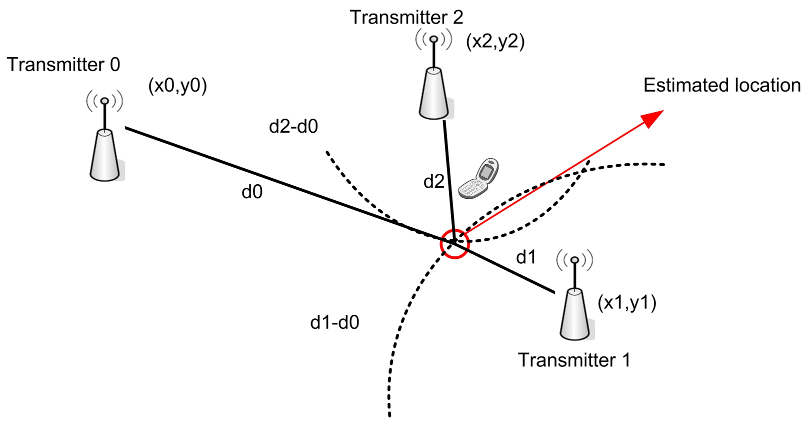

Figure 2.2: Time Difference Of Arrival positioning technique [29]

- *Time Of Flight (TOF)/ Time of Arrival (TOA)* uses signal propagation time, from the receiver to a transmitter, to measure distance [35]. TOA positioning technique is shown in Figure 2.3.

- Another localization technique is called *RSS (Received Signal Strength)*, which is based on power attenuation of signal propagation between the receiver and transmitter. The signal during propagation gets attenuated due to multipath fading, distance, barriers such as wall, floor, building and mountains [29].

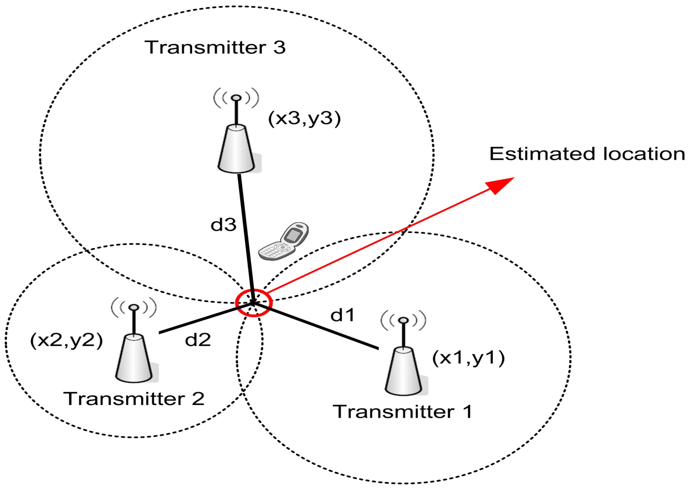

Figure 2.3: Time Of Arrival (TOA) technique [29]

- Another approach is called Phase of Arrival where the phase difference is used to calculate distance[15].

2.3.4 Scene Analysis

This method as shown in Figure 2.4 analyzes every observed scene in an area. Then the recorded views of the user are matched to the current measurement of the user's location [36]. Though the survey of the site before experimental is very exhaustive, the primary benefit of this technique is low cost [29].

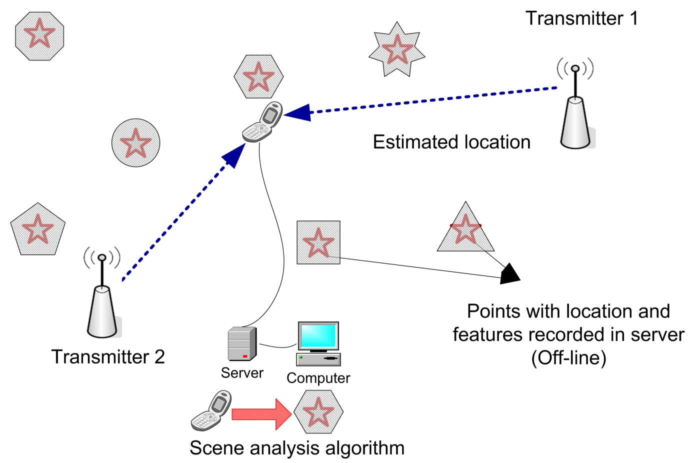

Figure 2.4: Scene Analysis Technique [29]

2.3.5 Dead Reckoning

The theory of this technique is based on some criteria such as information of the previous location, user's direction and distance covered by the user and the current location is measured using the elements mentioned above. According to Chen et al. [37], the equation of a dead reckoning positioning (Figure 2.5) system (where E = East, N = North and S = South) is as below:

$$E(t_n) = E(t_1) + \sum_0^{n-1} S(t_i)\sin(\theta(t_i))$$
$$N(t_n) = N(t_1) + \sum_0^{n-1} S(t_i)\cos(\theta(t_i))$$

In the equation $E(t_n), N(t_n)$ refer to current position and $E(t_1), N(t_1)$ are the previous one. The direction is expressed as $\theta(t_i)$ while covering the distance $S(t_i)$.

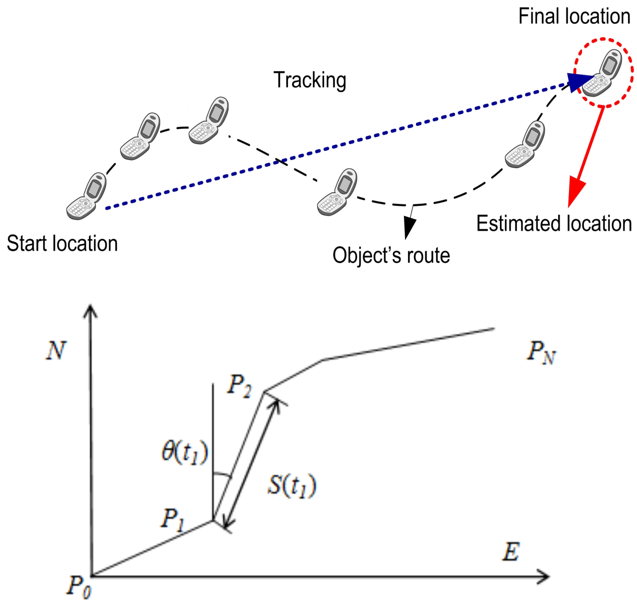

Figure 2.5: Dead Reckoning positioning method[29, 37]

2.3.6 Proximity

The principal of the proximity positioning technique (Figure 2.6) is based on the nearness of the user to the transmitter with a known position. Different types of sensors are used in the proximity localization method for the identification of users where transmitters could be indoor emitters such as RFID, Wi-Fi Access Points, Infrared signal [1]. It is a simple method, but the primary disadvantages are performance and accuracy. Therefore, the cost of the deployment increments as the quantity of sensors increases [36].

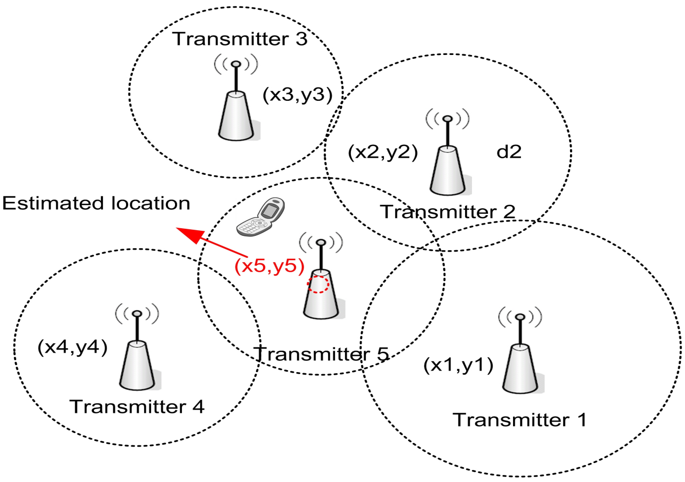

Figure 2.6: Proximity positioning technique[29]

2.3.7 Propagation Models

The strength of the transmitted signal decreases with the distance travelled by the radio signal [38]. In a free space model, if a radio signal arrives at a node after moving a distance x, then the attention of the signal is presented by $\frac{1}{x^2}$. *Rappaport* mentioned that path loss equation could be used to determine the RSS (Received Signal Strength) of the transmitted signal if the power of the signal is known. However, creating propagation models in an indoor environment is a challenge due to multipath effects and signal attenuation through walls and objects. Some models are designed for the specific area using empirical data such as SpotON 3D location sensing technology to overcome the problem [39]. Another example is RADAR [40] based on both empirical method and propagation model called WAF (Wall Attenuation Factor) works with the defined numbers of obstacles between receiver and transmitter; however, the performance of RADAR is not as accurate as empirical technique [28].

2.4 Signals used for positioning

Alternative signals as a signal of opportunity have the potential for indoor navigation due to having sufficient geo-location coverage [6]. The signals of opportunity are commonly used RF signals with higher power levels and broader area coverage that they can travel through barriers like walls of buildings whereas GNSS fails [7, 29]. There are some problems related to SoOp as they are not designed for positioning purposes; however, the cost-effectiveness of deployment of SoOp can win over the GNSS [41]. Recent utilization of several SoOP are such as Wi-Fi, Bluetooth, ZigBee, Ultrawideband, GSM signals used for mobile phone communication and DVB television signals [6, 29]. Moghtadiee [29] mentioned that synchronization is a precarious issue when SoOp such as Digital Audio Broadcasting (DAB), Digital Video Broadcasting (DVB), WLAN, are considered as ranging signal. As these SoOPs are based on Orthogonal Frequency Division Multiplexing modulation, therefore, for the deployment for ranging the known part of the OFDM symbol is used while the random part remains intact [29, 42].

2.4.1 Audio Bandwidth Signals

Recent studies show that analog and digital signals with audio bandwidths such as FM radio broadcast signals have been deployed for navigation purposes [13]. FM and AM radio broadcast signals are considered as analog signals where digital services are known as High Definition (HD) Radio. Based on the existing spectrum for FM radio services and due to some advantages such as utilization of current AM and FM frequencies, no requirements for a power upgrade and the compatibility to most existing receivers made digital radio popular in many countries [43]. Advantages of using these signals for localization include good signal reception indoor and outdoor and low-cost of hardware deployment. However, due to not having any timing information, FM and

AM face challenges which are crucial for range or position measurements. Also, lack of synchronization in time, phase, and frequency is an issue for FM transmitters [29]. Kelly [44] mentioned that deployment of a fixed position observer unit could solve the problems of no synchronization of transmitters. The observer unit receives transmitted signals from all radio transmitters from nearby locations, and regulates their phases and broadcasts the information of transmitter signals [44]. As FM or AM signals do not have any timing information, an additional receiver needs to be deployed in an FM or AM navigation system using trilateration techniques. Also, special hardware coupled with the multi-directional antenna is required to obtain direction and timing information [45]. However, an alternate solution to triangulation is known as position fingerprinting which had been implemented for FM experiments in [1] and [45]. Moghtadaiee mentioned that the fingerprinting method does not require any large infrastructure or extra hardware and is independent of the multipath effect in comparison to other distance-based techniques although the fingerprinting process is disadvantageous of being exhaustive labour intensive [29].

2.4.2 Television Signals

Television signals were first implemented with integrated GPS signals by Rosum Corporation for navigation purposes [46]. Due to some advantages such as low frequency, high transmission power, full frequency bandwidth, large area coverage capability, and minimum path loss, TV signal is an excellent choice for positioning purposes [47]. The latest Digital TV signals work together with Analogue TV signals as part of TV terrestrial service within VHF (Very High Frequency) and UHF (Ultra-High Frequency) bands [42]. As the analog TV signal has horizontal and vertical pulse synchronization and the digital signal has frame synchronization characteristics, Martone [46] suggested both signals can have a potential for navigation use. However, there is a significant drawback of TV signals which is scarcity of information of transmission time and the estimation of transmission time. This issue occurs with errors due to unstable clocks in TV transmitters; therefore, Rosum Corporation projected a model by setting up a regional monitor station to observe errors and transmit the rectified time information [46].

2.4.3 Wi-Fi

Due to low cost, high RF power, efficiently deployable solutions, WLAN is a good selection for indoor navigation. Most commonly used WLAN is known as Wi-Fi Network consists of Access Points (APs) and the Wi-Fi communication is based on IEEE 802.11b standard with a frequency range of 2.4GHz or 5GHz [4, 29]. Ekahau [26] and Skyhook [27] are the most widely used indoor position tracking systems integrated with Wi-Fi APs distributed in inhabited areas [27]. However, Wi-Fi signals are a short range with maximum coverage of 32 metres and are vulnerable to interference of signals such as ZigBee, Bluetooth and microwave ovens, security cameras and wireless LANs. Therefore the presence of these signals within range of APs diminishes the performance of Wi-Fi [29]. Indoor positioning based on Wi-Fi mostly uses RSS or fingerprinting methods [17, 29, 40, 48]. Despite the fact this technique requires extensive labour to collect data, however, consideration of NLOS and multipath effect provides a relatively high accuracy within the 3m range [49-51].

2.4.4 Bluetooth

Bluetooth is an affordable and popular technology that has short range communication capability with RF band of 2.45GHz ISM, minimum power consumption and high accuracy up to 1 meter [52, 53]. In general, several beacons are required for utilizing the fingerprinting method for positioning, and the connectivity of Bluetooth Beacons is secure like Wi-Fi. However, there are some issues with Bluetooth such as requirements for additional hardware and software applications and short-range coverage up to 30m.

2.5 Location Fingerprinting Techniques and localization Algorithms

The fingerprinting method is defined as a collection of RSS samples of the user's location, and the position is calculated based on the various mathematical algorithms such as Deterministic Approach [29, 40], probabilistic approach [54],and neural networks [28]. A fingerprinting system contains two phases: I) Training stage or Offline stage, and II) Positioning Stage or Online stage. The training phase consists of producing a database containing Reference Points (RPs) created by the user which includes location information parameters including location coordinates and *RSS* vectors from the allocated transmitters known as "fingerprint") [48]. In the positioning phase, the user's RSS vector (a fingerprint) is matched to the Reference Points (RPs) collected in the database of the training phase or Offline phase[13], and the proximity of the fingerprints between data in Offline and Online stage determines the position of the user.

I. Training Stage:

The primary activity of this stage is to construct a database for a set of positioning data identified as *R* Reference Points (*RPs*) where ($r = 1{:}\,R$) which consists of a number S samples of the (*rss)* Received Signal Strength. A maximum number of Q allocated AM radio channels (*CH*) provided the *rss* values for a specified period and then the total number of samples ($n = 1{:}\,S$) of the *rss* produces the averaged ($\overline{rss}$) values. Each data point in the database represents the location information in Cartesian coordinates in (x, y) based on two-dimensional space of the experimental site. The size of the database varies depending on the number of *RPs*, and Radio Channels used for this experiment. The database is defined as follows (1).

$$RP_{R(x_r,y_r)} = \left[\frac{1}{S}\sum_{n=1}^{S} rss_{CH1}^{n}, \frac{1}{S}\sum_{n=1}^{S} rss_{CH2}^{n}, \dots, \frac{1}{S}\sum_{n=1}^{S} rss_{CHQ}^{n}\right]$$

$$RP_{R(x_r,y_r)} = [\overline{rss}_{CH1}^{n}, \overline{rss}_{CH2}^{n}, \dots, \overline{rss}_{CHQ}^{n}] \tag{1}$$

II. Positioning Stage:

This stage works similarly to the training stage which measures the user's unknown position based on a database of positioning stage referred as Test Points (*TPs*). The current location of the user is found by *TPs* which are compared to the *RP* database using some standard algorithms such as Nearest Neighbour (*NN*), K-Nearest Neighbour (*KNN*) and K Weighted Nearest Neighbour (*KWNN*). Therefore, the notation of the positioning can be described as a set of *T* Test Points (*TPs*) contains the average *rss* values $\overline{rss}$ of $\acute{S}$ number samples ($\acute{n} =$

$1{:}\acute{S}$) with a specified time ($t = 1{:}T$) obtained from the $\acute{Q}$ specified AM radio channels (CH),[14]. The total number of AM channels $Q = \acute{Q}$ because the experiment uses an equal number of AM radio channels for both *TP*s and *RP*s Then the *TP* equation is as follows (2).

$$TP_{T(x_t,y_t)} = \left[\frac{1}{\acute{S}}\sum_{\acute{n}=1}^{\acute{s}} rss_{CH1}^{\acute{n}}, \frac{1}{\acute{S}}\sum_{\acute{n}=1}^{\acute{s}} rss_{CH2}^{\acute{n}}, \dots, \frac{1}{\acute{S}}\sum_{\acute{n}=1}^{\acute{s}} rss_{CH\acute{Q}}^{\acute{n}}\right]$$

$$TP_{T(x_t,y_t)} = [\overline{rss}_{CH1}^{\acute{n}}, \overline{rss}_{CH2}^{\acute{n}}, \dots, \overline{rss}_{CH\acute{Q}}^{\acute{n}}] \quad (2)$$

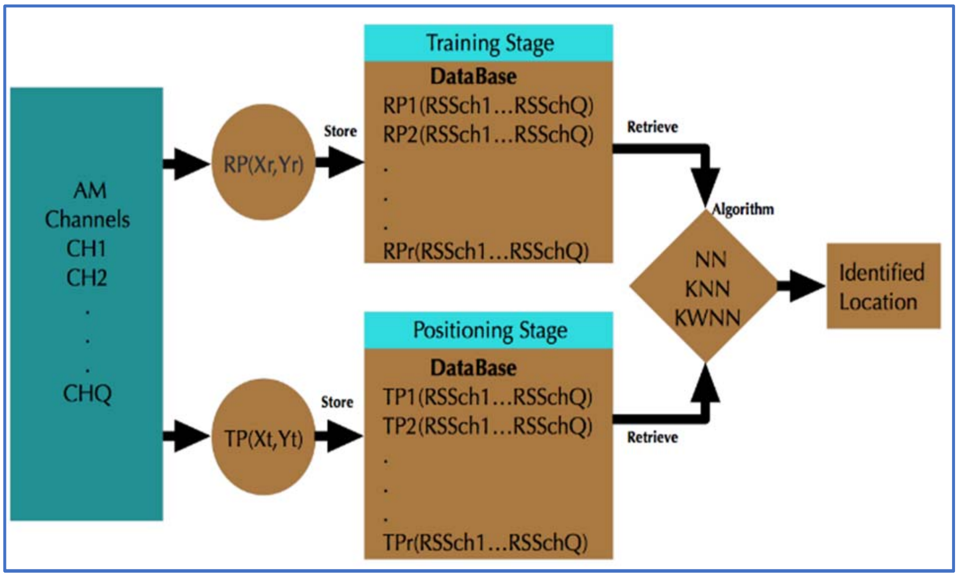

Figure 2.7. Fingerprinting System flowchart based on deterministic approach

In the positioning phase, a user's position can be determined based on two types of positioning approaches: a) Deterministic Approach b) Probabilistic Approach [13].

2.5.1 Deterministic Approach:

As the RSS or fingerprints vary because of environmental effects, therefore, the deterministic approach considers the RSS values by averaging them. Then the deterministic approach processes the data for finding a location based on algorithms such as Nearest Neighbour (NN), KNN (K Nearest Neighbour) and K Weighted Nearest Neighbour [1]. With the help of various distance measurement equations, the distance between two points known as Reference Point (fingerprints of user's location at the pre-processing stage) and Test Point (fingerprints of user's location at post-processing stage) are calculated. It has been found in previous studies that the KNN and KWNN perform better than NN with higher accuracy; however, the NN method can be better where RPs are distributed with considerable distance [29]. We implement the deterministic approach in this experiment because of the method's simplicity. The deterministic approach performs the location estimation of the user based on three standard algorithms *NN, KNN* and *KWNN* as mentioned in the literature review. Firstly, to find a TP or user's unknown location, the *NN* algorithm searches the nearest neighbour of its fingerprint or the closest *RP*, using their average *rss* values stored in the database and then the distance between the *TP* and *RP* is measured by Euclidean or Manhattan distance equation. Figure 1 shows the system diagram of fingerprinting technique using the deterministic approach. The equation of Euclidean distance [13] is as follows (3):

$$D_{Euclidean} = \sqrt{\sum_{i=1}^{p}\left(TP_{T(x_t,y_t)} - RP_{R(x_r,y_r)}\right)^2}$$

or

$$D_{Euclidean} = \sqrt{\sum_{i=1}^{p}\left(\overline{rss}_{CH\acute{Q}}^{\acute{n}} - \overline{rss}_{CHQ}^{n}\right)^2} \tag{3}$$

The second method is known as the K Nearest Neighbour (KNN) which finds the location by averaging the coordinates of the K nearest points of RPs [40]. Weighted averages of coordinates of the K nearest neighbours are considered for measuring the location of the K-Weighted Nearest Neighbour (KWNN) algorithm where the inverse of the distance defines the weights[1, 14]. A Wi-Fi fingerprinting experiment carried out by Li [5] presented that the *NN* method provides less accuracy than *KNN* and *KWNN*; however, this criterion is not universal because the accuracy also depends on the distances between RPs. In most cases, larger distances between RPs produce higher accuracy for the *NN* method [5].

2.5.2 Probabilistic method:

Unlike the deterministic approach, the probabilistic method does not consider averaging *RSS* or location fingerprints. Instead it creates the model of location fingerprint using conditional probability and then the user's position is estimated by Bayesian interference [28, 29, 54]. The conditional probability $P(L_i|\bar{O})$ is calculated by Bayes theorem which determines the estimated position of TP [54]. The Bayes theorem can be expressed as

$$P(L_i|\bar{O}) = \frac{P(\bar{O}|L_i)P(L_i)}{P(\bar{O})}$$

where $P(L_i|\bar{O})$ is likelihood function and L_i denotes the location vector with $\bar{O}$ observation vector[13].

2.5.3 Neural networks:

The whole fingerprinting system is considered as a neural network, and a Multilayer Perceptron (MLP) calculates the weights of the network. The weights apply to a user's fingerprints or RSS vector, and the user's location is identified by the transfer function [29, 55]

2.6 Fingerprinting Vector Distance Measurements

To find a user's current position TP (Test Point) concerning the closest RP stored in the database, a distance measurement between TP (user's current location) and the nearest RP is measured based on various distance calculation equations known as vector distance.

2.6.1 Minkowski Distance

Minkowski distance (2.1) is defined by the distance between two points such as TP and RP. Depending on the norm parameter, the distance definition is changed which means when the value of norm parameter q=1 the vector distance is known as Manhattan distance (2.2) and for q=2 the Euclidean distance(2.3) (2.3) [29, 56]. The Minkowski Distance is as below

$$D_{Minkowski} = \left(\sum_{i=1}^{p} \left|TP_{x_{t,}y_t} - RP_{x_{r,}y_r}\right|\right)^{\frac{1}{q}} \quad 2.1$$

$$D_{Manhattan} = \sum_{i=1}^{p} \left|TP_{x_{t,}y_t} - RP_{x_{r,}y_r}\right| \quad 2.2$$

$$D_{Euclidean} = \sqrt{\sum_{i=1}^{p} \left(TP_{T(x_t,y_t)} - RP_{R(x_r,y_r)}\right)^2} \quad 2.3$$

Chapter 3

Fingerprinting Technique For Indoor Localization Using AM Radio Signals

3.1 Introduction:

In this chapter, we introduce a new fingerprinting method for indoor navigation with the means of Amplitude Modulation signals, and the results of the experiment are compared to the FM fingerprinting [1, 13, 29] method previously conducted by Moghtadaiee [29]. The reasons behind utilizing AM signals for indoor localization is that AM signals have some advantages such as signal availability, high RF power, low cost, lower sensitivity to the indoor environment. Firstly, high transmission power makes the AM signals receivable in almost every outdoor and indoor environment. The free availability of AM signals, without any need of infrastructure or massive deployment of hardware, is another plus point of AM signal whereas Wi-Fi, Bluetooth or beacons require significant implementation of hardware and software infrastructure for indoor navigation. To develop a Wi-Fi or beacons based localization system requires several Access Points (APs) across the experimental site as better the number of APs better the presence of signal across the site. Therefore, AM fingerprinting costs are low because it only requires an AM radio receiver in comparison to other signals. Interference to Wi-Fi signal such as microwave ovens, mobile phones or Bluetooth devices are common but the AM band is independent, and there should be no non-AM interferences in the band [29]. Signal propagation modelling based approaches can be used for positioning. However, multipath and other environmental effects, such as materials and structure of the building, cause significant attenuation of the propagated signal. These issues can also destabilize the signal propagation model for indoor navigation [5] and because of its low frequency an AM signal does not fluctuate over short distances like the Wi-Fi signal during propagation within the indoor or crowded environment, which makes AM stable for indoor navigation.

On the other hand, AM signal has the disadvantage of having no timing information which is crucial for direct position measurement [44]. Though the AM transmitters broadcast strong AM signals, the long wavelength and small bandwidth of AM signals cause some problems. Our experiment and survey observed that the structure of the building has significant influence over the AM signal's presence and RSS fingerprints inside the building [14]. FM signals in past research showed the impracticality of indoor navigation using TOA, AOA or TDOA methods without synchronization and timing information [13]. An AM signal also has similar properties of no timing information. Considering the factors related to FM, we need to eliminate those issues, and therefore, this research proposed to perform indoor navigation using the RSS technique. The reasons why the fingerprinting method can avoid the problems related to FM or AM signal localization are as follows. Firstly, fingerprinting is low cost due to no requirement for infrastructure or additional hardware [29, 45]. Secondly, fingerprinting is a straightforward way to perform indoor localization in compare to TDOA or TOA as FM/AM do not have any timing information [1]. Though mapping floor, collecting fingerprints data and building database are laborious and significantly time consuming work [14, 57], it is less prone to continual data update and does not require regular updates due to replacement or relocation of APs like Wi-Fi [29]. Finally, to the best of our knowledge, this investigation is taking place for the first ever to conduct indoor localization using AM signals.

An experiment with AM signals using TDOA for navigation purpose was conducted by McEllroy et al. [58], where they deployed Software Defined Radio(SDR). The results were assessed based on signal strength, measurement accuracy for correlation peak shape and signal to noise ratio, availability of signals which is referred as signal diversity, signal-to-noise ratio (SNR) and multipath effects in the outdoor area. The study considered Time Difference of Arrival (TDOA) positioning technique for calculating the location and achieved accuracy of 20m [58].

Some research was conducted on FM fingerprinting and the first was carried out by Youssef [59] where they utilized a prototype watch integrated with FM radio receiver to measure location fingerprints from seven radio stations in an urban location. The performance of the study was not very practical regarding accuracy as the as median error of 8 kilometers was very high in comparison to other experiments [59].

A most recent experiment utilizing FM fingerprints was completed by Moghtadaiee [13] where the results were compared to the performance of Wi-Fi. The analysis of results was illustrated via deterministic and probabilistic approach with four perspectives such as mean distance error (MDE), data acquisition time, sensed channel number, and the number of reference points [13]. The author also introduced a novel technique called the hybrid or combined method which is a mix of the best deterministic approach (KWNN algorithm) and the best probabilistic approach (Histogram method). The combined process performed with the best accuracy with the lowest MDE of 2.48m [13].

The previous study on AM signals was for outdoor navigation and accuracy was not very acceptable in comparison to FM or Wi-Fi signal; however, our experiment is considering AM signals for the indoor environment with an expectation of achieving higher accuracy. To have a better insight of the mechanism of the deterministic approach in the fingerprinting method, this chapter explains the experiment and results by comparing three different methods: NN, KNN and KWNN. Analysis of the results in this chapter also focuses the impact of the positioning accuracy based on the frequency and spatial diversity caused by the reduction of the number of frequency channels and transmitters allocated for the experiment. Finally, we investigated the effect of reducing the number of RPs on the accuracy and the reason of NN's best performance over KWNN. The content of this chapter produced the following publication:

1. M.M. Rahman, V. Moghtadaiee, and A. G. Dempster, "Design of Fingerprinting for Indoor Localization Using AM Radio Signals," *in Proc. Of IEEE Indoor Positioning and Indoor Navigation (IPIN), Sapporo, Japan, Sep.2017, pp.1-7*

3.2 EXPERIMENTAL SETUP

3.2.1 Experiment

The experiment for this research was conducted on the UNSW campus. The site was divided into two floors, ground floor and the first floor of building G6, the Block House, and the location is a classroom environment including desks and chairs, corridors, disabled and male-female toilets. The size of the test bed is 28m by 12m as shown in the Figure 3.2a and Figure 3.2b. The whole experiment was performed in an indoor environment; therefore, the testbed does not carry any longitudinal and latitudinal information instead the testbed uses a local (x, y) coordinate system. The location system in the experiment contains in total 51 Reference Points (RP), and 20 Test Points (TP) where RPs and TPs are marked in red and blue respectively. The ground floor consists of 29 RPs with 13 TPs, and the first floor has 22 RPs with 7 TPs. Due to security issue and occupancy of classroom materials, some of the rooms on both floors have restricted access and movability to every corner , therefore, the distribution of RPs and TPs are not always even compare to the previous experiment [13]. This experiment considers a total of 8 Sydney-based AM radio stations (see Table I.) with the most reliable reception. According to Australian frequency spectrum, AM radio broadcast channels are allocated in the frequency range of 526.5kHz-1606.5kHz (see Figure 3.3)[60, 61].

AM Radio Stations	*Frequency (kHz)*
Radio National	576
ABC News Radio	630
702 ABC Sydney	702
2GB	873
2UE	954
Sky Sports Radio	1017
SBS Radio	1107
2CH Easy Classics	1170

TABLE I. List of AM Radio channels used in the experiment [61].

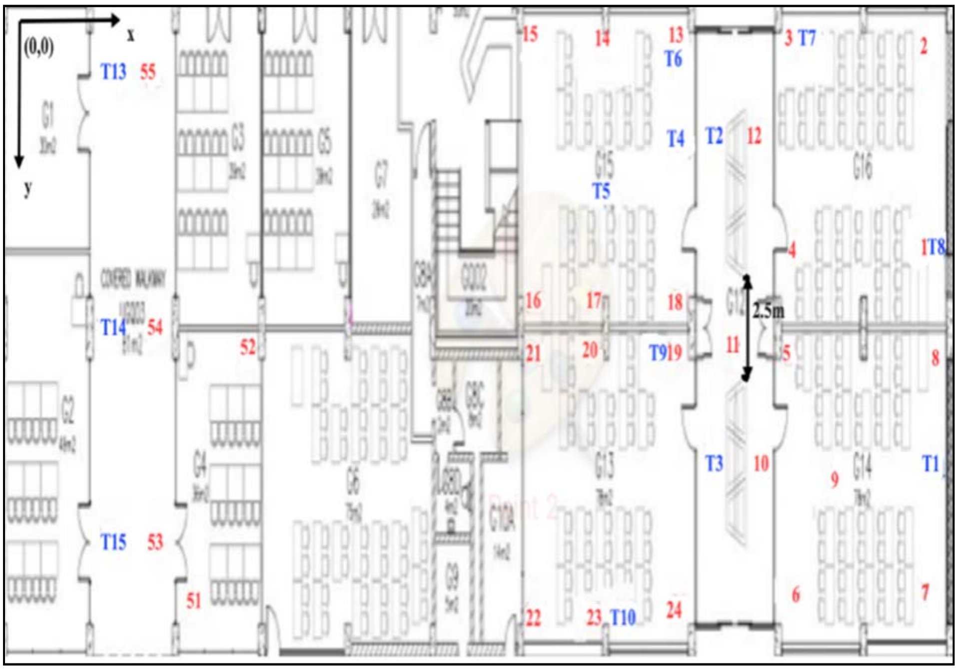

Figure 3.2a. Experimental test bed at Ground Floor

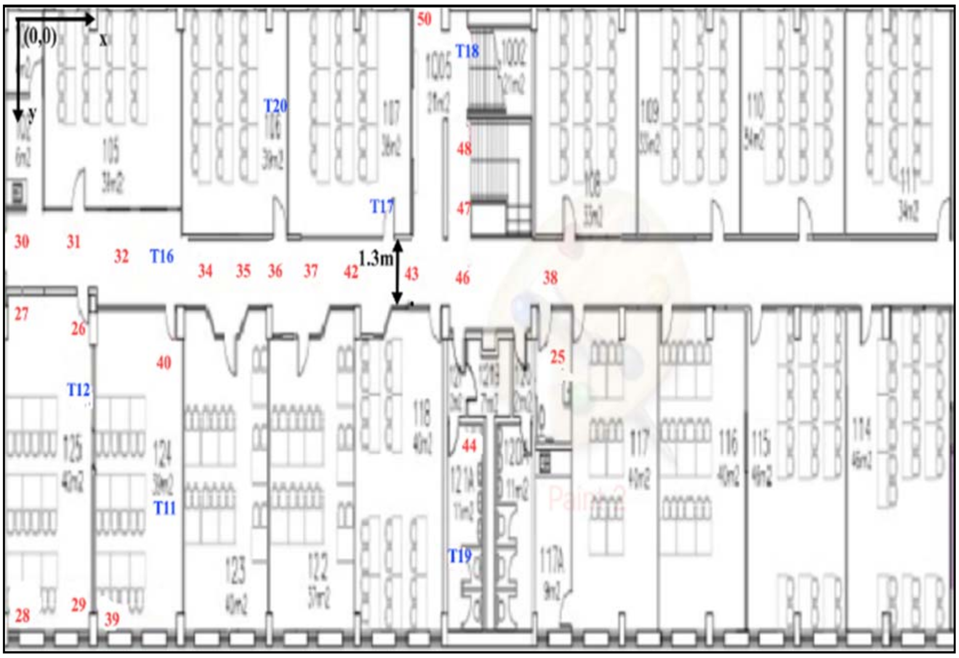

Figure 3.2b. Experimental test bed at First Floor

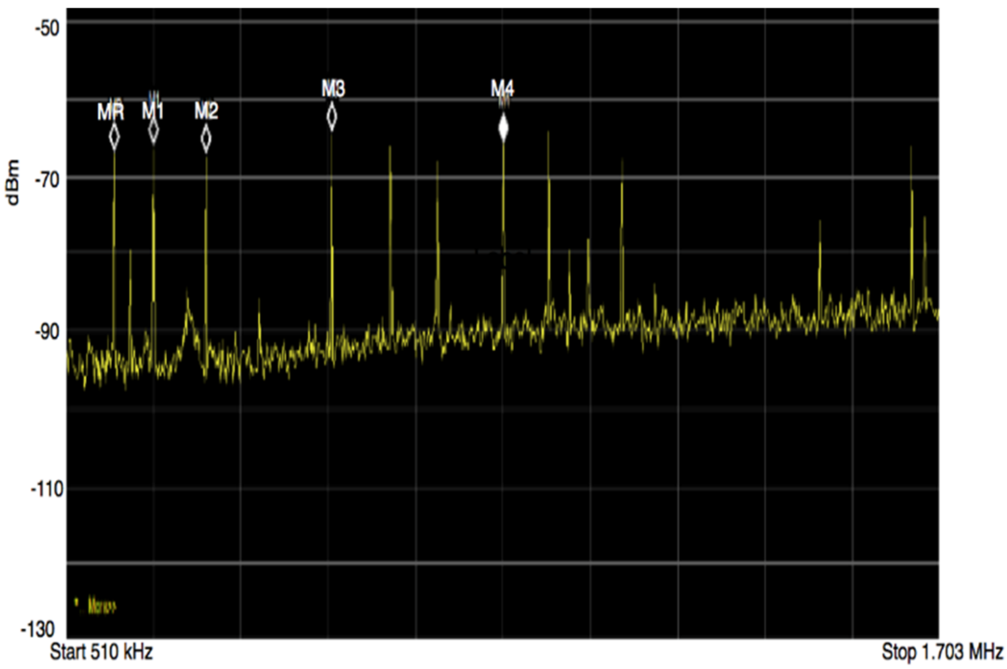

Figure 3.3. FFT of major AM radio broadcasting channels across Sydney

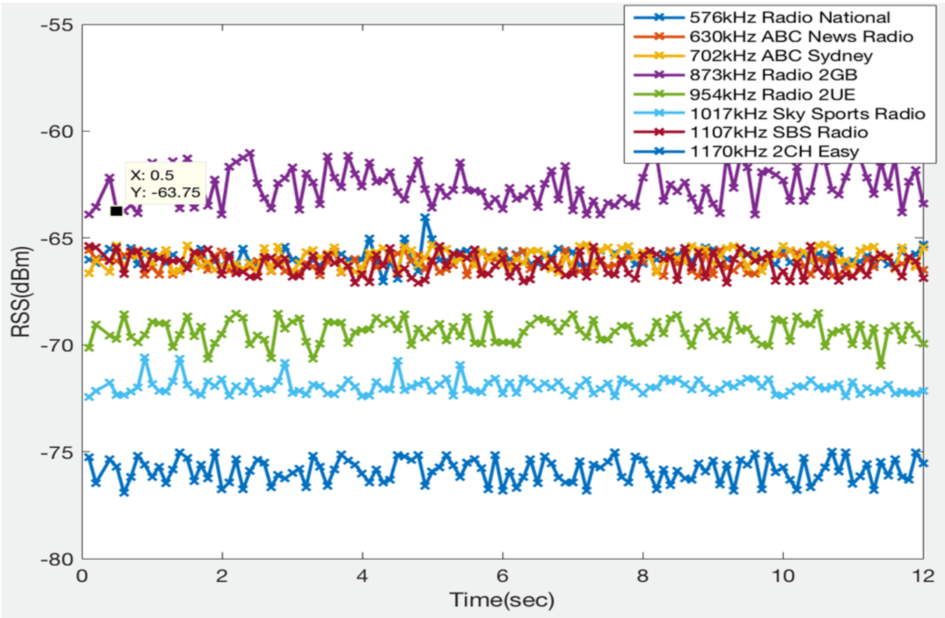

Figure 3.4. Variation of RSS of eight AM channels for 12 seconds at one Reference Point (RP)

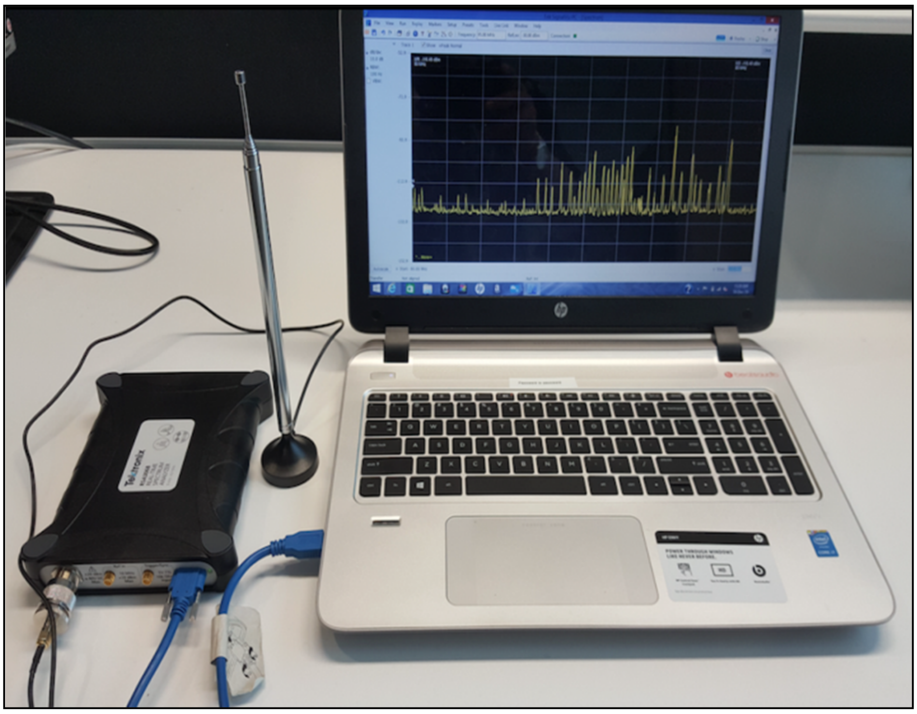

Figure 3.5. Tektronix RSA306 Real Time Spectrum Analyzer connected with SignalVU-PC software

It is normal to see variation in the sampled RSS as variation is gained from noise, multipath and changes in RF propagation. For each RP and TP, 12 seconds were allocated for measuring RSS samples, and 120 measurements were taken during the experiment (Fig 3.4), and the test took place after hours when students and staff were not present [14].

3.2.2 Data Acquisition

A Tektronix RSA306 USB Real Time Spectrum Analyzer was used for this experiment which is operated by signal acquisition and analysis software SignalVU; these products are developed by Tektronix (see Figure 3.5). The device has the capability of receiving and analyzing a frequency range from 9kHz to 6.2GHz, and it can also measure signal power range from +20 dBm to -160dBm with a maximum sampling rate of 112 Ms/s [62]. To receive the signal in the spectrum analyzer, we used a telescopic AM radio antenna. We saved our measurements in Matlab compatible files, for analyzing later in Matlab software [63].

3.3 Experimental Results and Analysis

This section details the analysis of results gained from the experiment and the investigation of data is based on two conditions: K value and number of channels. To measure the errors between the actual or Test Point's position and the estimated position, we utilised Euclidian distance. Mean Distance Error (MDE) is used as an error indicator which includes the mean of all measured errors from the three algorithms NN, KNN and KWNN [1]. The relationship between the MDE and K values of NN, KNN and KWNN is shown in Figure 3.6a and Figure 3.6b.

In Figure3.6a the NN algorithm has upward trends of MDE with the value of K=1 while the measurements are considered for the ground floor with the best performance from the lowest Mean Distance Error. The result on the ground floor shows that the lowest MDE of 2.76m is achieved while the value of K=1 has the best performance from the NN algorithm. It also means that during the position estimation the MDE in NN method considered only a single nearest or closest neighbour (K=1) around the RP. The observation for K=2 from the Figure 3.6a shows that KWNN resulted in the second-best performance with the second lowest MDE of 3.0m whereas the KNN has 3.3m.

Ground Floor	*NN*	*KNN*	*KWNN*
MDE	2.76m	3.295m	3.04m
CDF 69.23%	4m	5.5m	4m
CDF 100%	5.5m	7m	7m
First Floor	*NN*	*KNN*	*KWNN*
MDE	2.954m	3.643m	3.319m
CDF 85%	5m	5.5m	5m
CDF 100%	6m	7.7m	6.5m

TABLE II. Errors for three algorithms when k=2

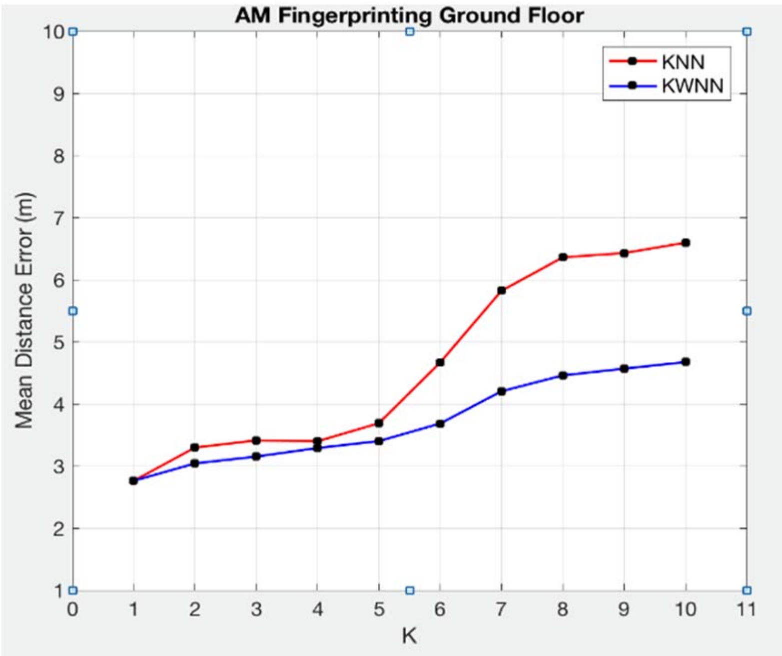

Figure 3.6a. The relationship between Mean Distance Error (MDE) and K values of NN, KNN and KWNN methods for Ground floor

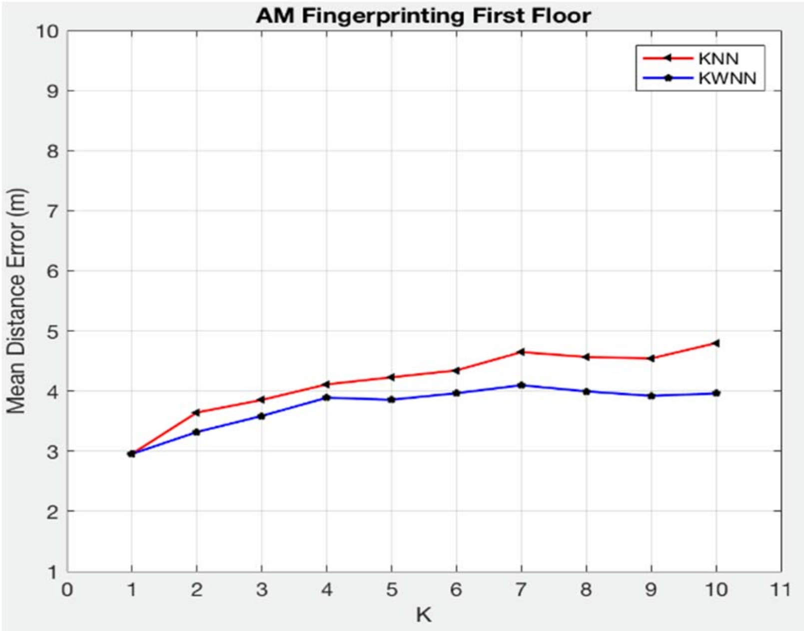

Figure 3.6b. The relationship between Mean Distance Error (MDE) and K values of NN, KNN and KWNN methods for the first floor

In Figure 3.6b we can see the NN method finds the lowest MDE of 2.954m with K=1 in the first floor which is 19.4cm more error than the ground floor. At the same time, KNN and KWNN have an increasing trend for MDEs in the first floor which is like ground floor. The KWNN algorithm shows improved performance than the KNN though the NN method has superior accuracy in Figure 3.6a and Figure 3.6b.

The Cumulative Distribution Function (CDF) of distance error when K=2 for two floors is shown in Figure 3.7a and Figure 3.7b. Considering the ground floor, NN presents the highest error of 5.5m on the as opposed to KNN and KWNN having 7m. In the CDF of 61%, KWNN and KNN demonstrate the higher probabilities of less error at 3m compare to NN. The KWNN presents better performance between the percentiles of 40th and 70th whereas NN method shows the same error at 3m in the 53.85th percentile of CDF. On the other hand, TABLE II for the first floor shows that the KNN has the maximum error of 7.7m and NN has the minimum of 6m whereas KWNN with 6.5m. Our investigation found that the results of accuracy for the NN performed best initially, however, in the later part of the analysis we illustrated how the arrangement of RPs affected the performance of the accuracy of our positioning depending on the number of RPs on each floor.

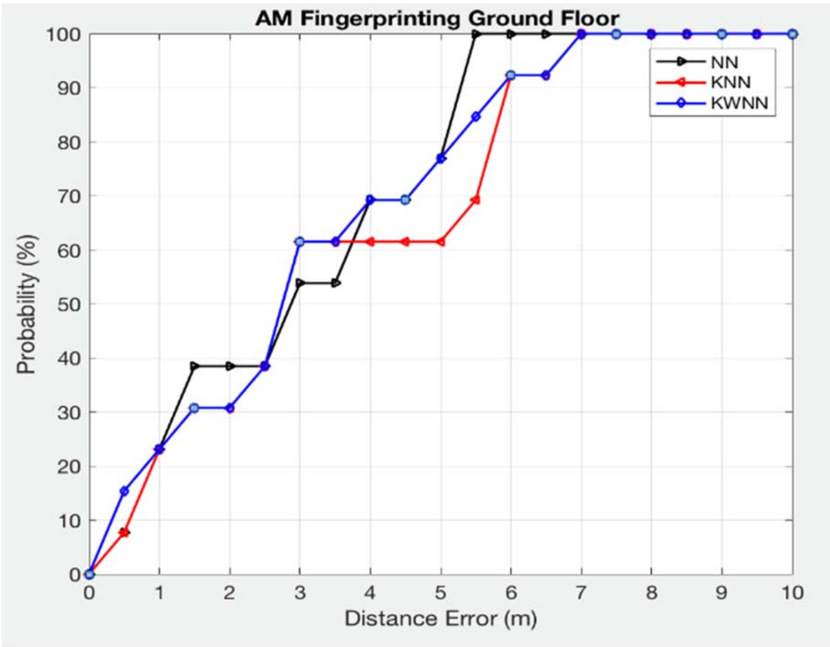

Figure 3.7a. Cumulative Distributed Function of NN, KNN and KWNN algorithms (K=2) for Ground Floor

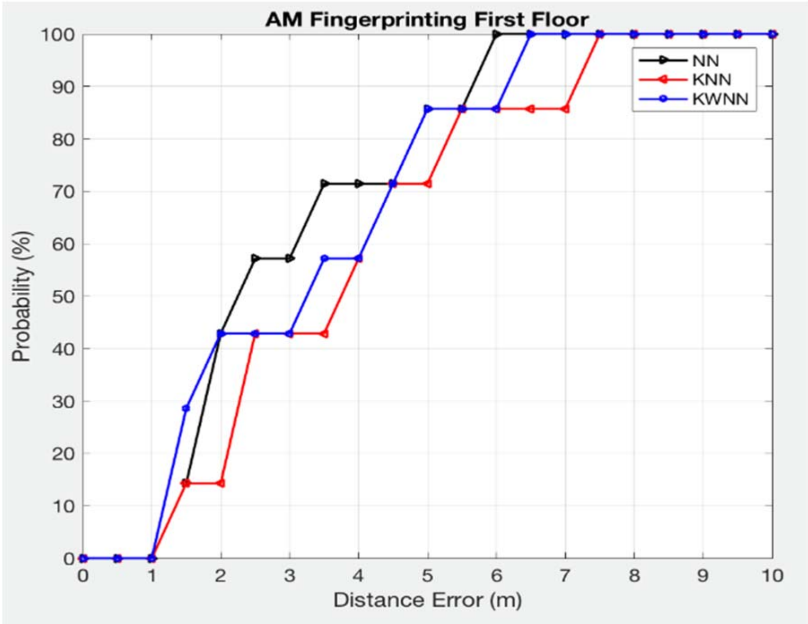

Figure 3.7b. Cumulative Distributed Function of NN, KNN and KWNN algorithms (K=2) for the first Floor

Ground Floor	*NN*	*KNN*	*KWNN*
8 Channels (MDE)	2.76m	3.295m	3.04m
4 Channels (MDE)	4.2m	3.346m	3.326m
First Floor	*NN*	*KNN*	*KWNN*
8 Channels (MDE)	2.95m	3.643m	3.319m
4 Channels (MDE)	3.044m	3.616m	3.44m

TABLE III. MDE comparison for errors by reducing 50% of total number of channels

We implemented a total of 8 major AM broadcasting channels for this experiment. We also investigated the frequency diversity of AM fingerprinting as we found some of the transmitters broadcast multiple channels from a single antenna. Therefore, frequency diversity allowed us to analyse the impact of the number of channels or frequencies on the positioning performance. Initially, the number of channels was reduced to 4 which is 50% of the total number of channels allocated for a single transmitting antenna, and Table III presents the comparison between the results affected by the reduction of some

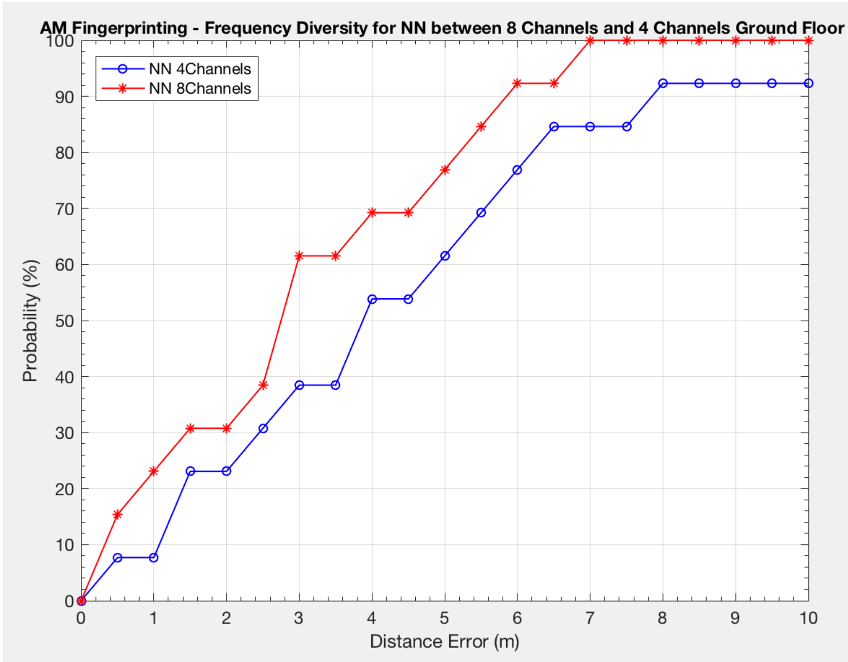

Figure 3.8a. CDF of NN for Frequency Diversity between 8 and 4 channels on Ground floor

channels from 8 to 4 in both floors. On the ground floor, the output from the Table III shows that the KWNN algorithm gives best MDE for 4 channels with smallest mean distance error difference of 28cm compared to the output of 8 channels. Nevertheless, considering the first floor, the NN algorithm showed the best MDE with the least variation of 9.4cm. The NN method on the ground floor performs better with significant of error probabilities demonstrated in CDF (see Figure 3.8a); however, the error difference for KWNN method between 8 and 4 channels is not very significant as shown in MDE comparison (see Table III), but the error probabilities in CDF (see Figure 3.8b) for KWNN show the visible difference of error achieved from frequency diversity between 8 channels and 4 channels. The decline of accuracy after reducing the number of channels from 8 to 4 is shown in Figure 3.8a and Figure 3.8.

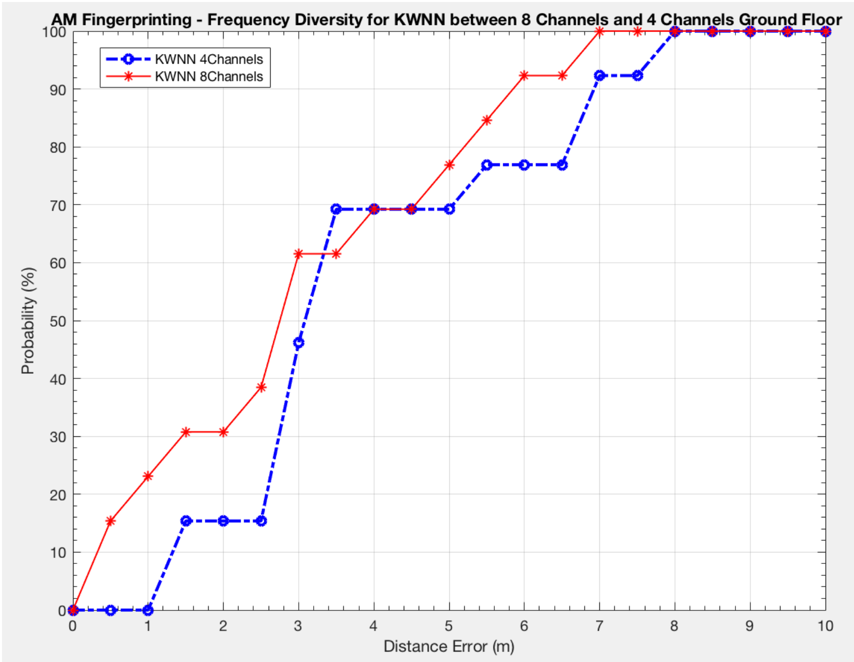

Figure 3.8b. CDF of KWNN on the ground floor Frequency Diversity for 8 and 4 channels

Ground Floor	*NN*	*KNN*	*KWNN*
8 Channels (MDE)	2.76m	3.295m	3.04m
5 Channels (MDE)	3.21m	3.255m	3.028m
First Floor	*NN*	*KNN*	*KWNN*
8 Channels (MDE)	2.954m	3.643m	3.319m
5 Channels (MDE)	3.21m	3.549m	3.183m

TABLE IV. MDE comparison for Spatial Diversity using the 5 channels transmitted from 5

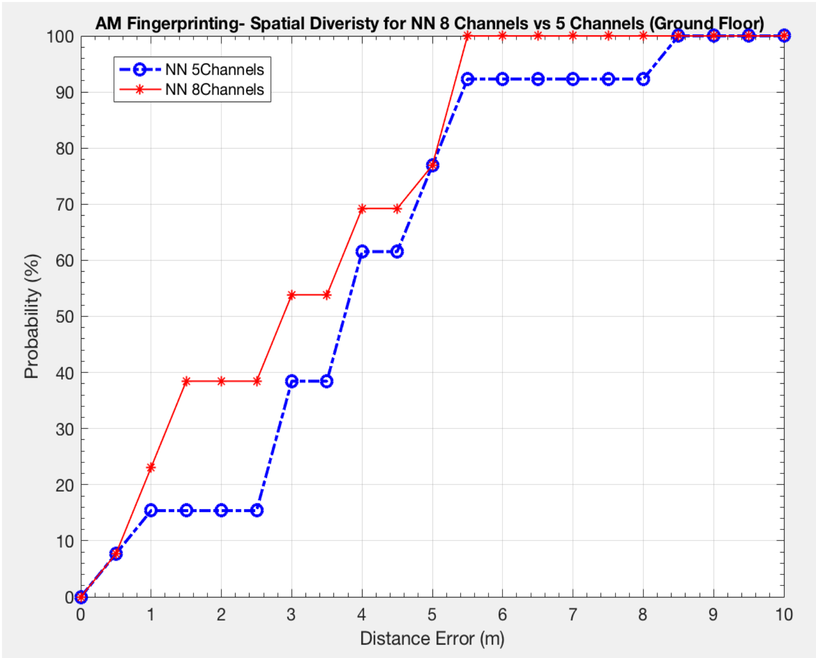

Figure 3.9a. CDF of NN algorithm for Spatial Diversity when 5 channels transmitted from 5 different antennas

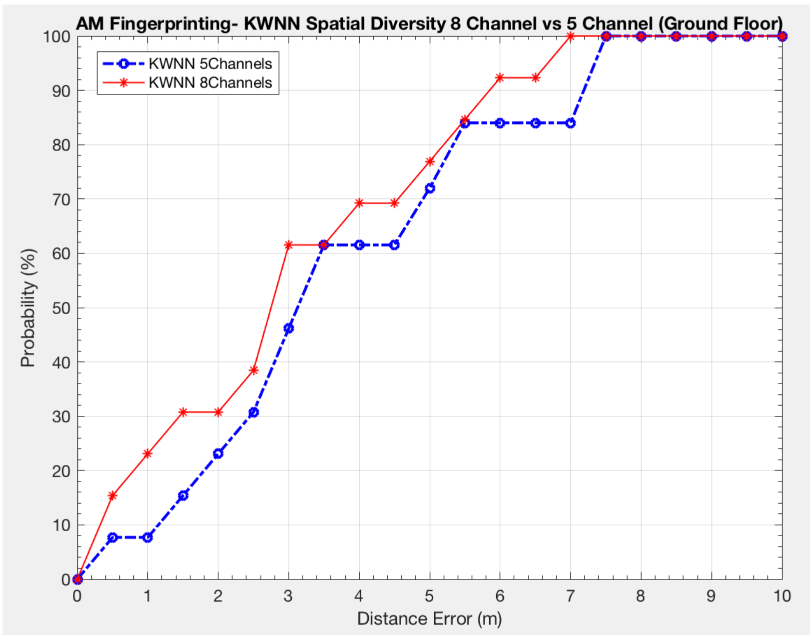

Figure 3.9b. CDF of KWNN algorithm for Spatial Diversity when 5 channels transmitted from 5 different antennas.

Secondly, our selection of only 5 channels transmitted from 5 individual transmitters is considered to examine the spatial diversity [57]. Table IV shows that 5 channels for the ground floor have 3.028m of lowest MDE which is slightly higher than 8 channels, on the contrary, the first floor achieved only 22.9cm. Although the CDF of Figure 3.8a and 3.9b present a visible difference of accuracy due to decreasing the number of channels from 8 to 5 for NN and KWNN, the differences of MDE due to spatial diversity are not very significant. Through the comparison of spatial diversity between 8 channels and 5 channels concludes that higher number of channels results in better positioning accuracy even if the channels are transmitted from the same transmitter.

Another crucial factor that we are interested to investigate is the decreasing the number of RPs by the rearrangement of RPs across two floors, so that we can better understand the effect of the density of RPs on the accuracy of fingerprints. Therefore, the variation of accuracy on the position estimation by varying number of RPs would enable us to investigate whether the system needs a increment of RPs to improve the accuracy. In this part, the assessment of MDE is based on decreasing the number of RPs. As there is small set of RPs allocated on both floors, therefore, we intentionally reduce the number of RPs by small sets such as 23,17,13 for the ground floor and 16,12,10 for the first floor. The set of RPs are removed in such way that all the RPs are evenly distributed and having no large distance between RPs and TPs. The sets of RPs for the ground floor are reduced with a large portion in compare to the first floor because the number of RPs are larger than the RPs in the first floor and the floor plan of the ground floor is wider and open than the first floor with narrow corridor, lift, disabled and male/female toilets. The output generated four databases (including original number of RPs before reduction) for each floor.

Figure 3.10 and 3.11 show the MDE of both floors gained from the variation of number of RPs by NN, KNN and KWNN Algorithms. It is visible in most cases that the decreasing number of RPs has the impact on lowering the accuracy, i.e. the increasing trend of number of RPs improves the accuracy. Considering the result on the ground shown in Figure 3.10, the NN method has the worst accuracy as the number of RPs decreases, though it started with the best result at the beginning. On the contrary, the KNN and KWNN illustrates decreasing rate of accuracy but both behaved very consistent in compare to NN. Conventionally, we expected KWNN should preform best at the beginning of test with full number of RPs. However, later we investigated that NN performed best where the reason is due to significant variation of RSS of a specific channel from RP to RP (shown in Figure 3.11a.3.11b, 3.11c and 3.11d). As the number of RPs on the first floor is small, therefore, we removed small sets of RPs. The result was very surprising with 12 RPs where the NN method showed sharp decrease in accuracy to the lowest level. Despite the decrement of accuracy, the KWNN method started behaving normal by showing best performance after removing the first 6 set of RPs from the test, which means either the arrangement of RPs across the floor or the multipath effect due to building structure has the impact on our initial result. The TABLE V. shows MDE for three algorithms after reducing number of RPs.

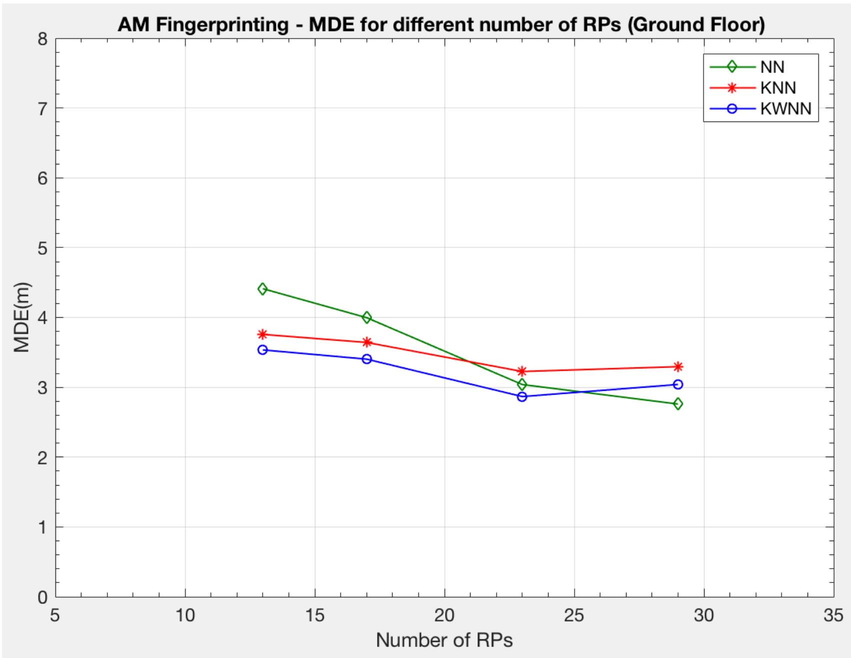

Figure 3.10. MDE after reducing number of RPs on the Ground floor

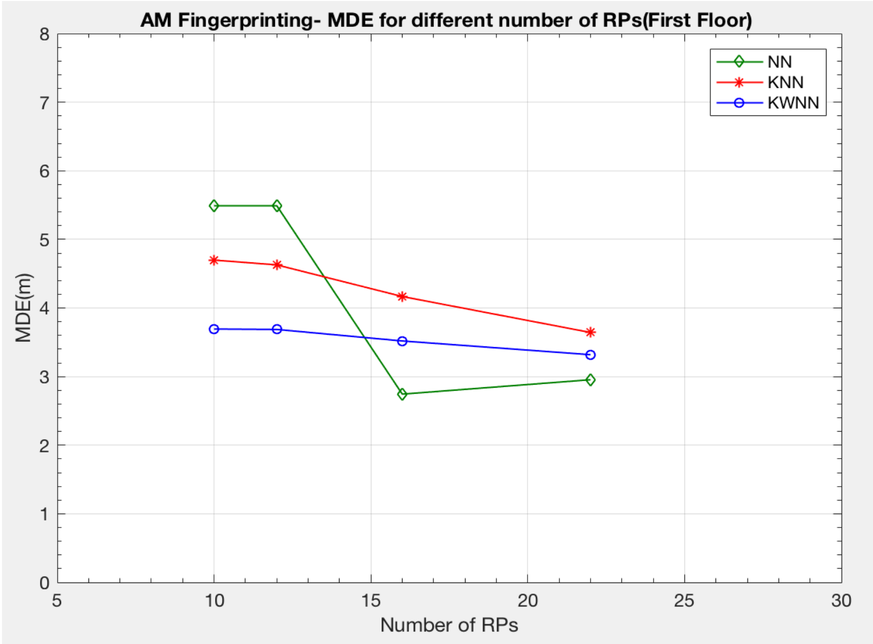

Figure 3.11 MDE after reducing number of RPs on the First floor

Ground Floor	*MDE(m)*		
Number of RPs	*NN*	*KNN*	*KWNN*
29	2.76	3.295	3.04
23	3.039	3.226	2.867
17	3.997	3.642	3.403
13	4.412	3.757	3.535
First Floor	*MDE(m)*		
Number of RPs	*NN*	*KNN*	*KWNN*
22	2.954	3.643	3.319
16	2.744	4.167	3.519
12	5.49	4.628	3.687
10	5.49	4.698	3.693

TABLE V. MDE for varying number of RPs on two floors.

In this part of the analysis, we are more concerned about the NN's behaviour rather than the decrement of its accuracy. To evaluate NN's best performance based on the full number of RPs, we plotted the histograms of RSS of 5 RPs and reduced number of RPs within a small region (RPs are relatively close to each other) of the test on both floors. Figure 3.11a shows that the variation of RSS from RP to RP for channel 1(576kHz Radio National) within the small region varies a lot and we can predict that the reason of this significant variation is due to multipath, the structure of the building and other barriers within the rooms. The signal difference between RP24 and RP11 (see Figure 3.11a) is 10dBm which is relatively high in comparison to signal difference between RP10 and RP11. Also, RSS of another pair such as RP14 and RP17 are around 5dBm away from RP10, RP11, and RP24. However, the expected RSS concentration of channel 1 in a stable condition is between -55 to -65dBm which is visible in Figure 3.11b and the signal strength of RP2, RP3, RP5, RP8, and RP12 do not vary a lot from each other after the removal of 16 RPs from the ground floor. On the other hand, RSS in the first floor behaved worse than the ground floor (see Figure 3.11c) where the signal strength of RP26 and RP27 is 20dBm stronger than RP30, RP32 and RP34. Once the 12 RPs are removed within the selected small region (RPs are relatively close to each other) of the first floor, the KNN gained higher accuracy due to have less difference of RSS from RP to RP presented in Figure 3.11d. Though the signal strengths of 4 RPs such as RP44, RP47, RP48, and RP50 (after removing 12RPs from the first floor) are not very strong due to the low signal presence, the difference of RSS from RP to RP is reasonable within 10dBm. The significance of these 4 RPs is that their RSS (see Figure 3.11d) concentrated within -85 and -95dBm rather than of scattered apart.

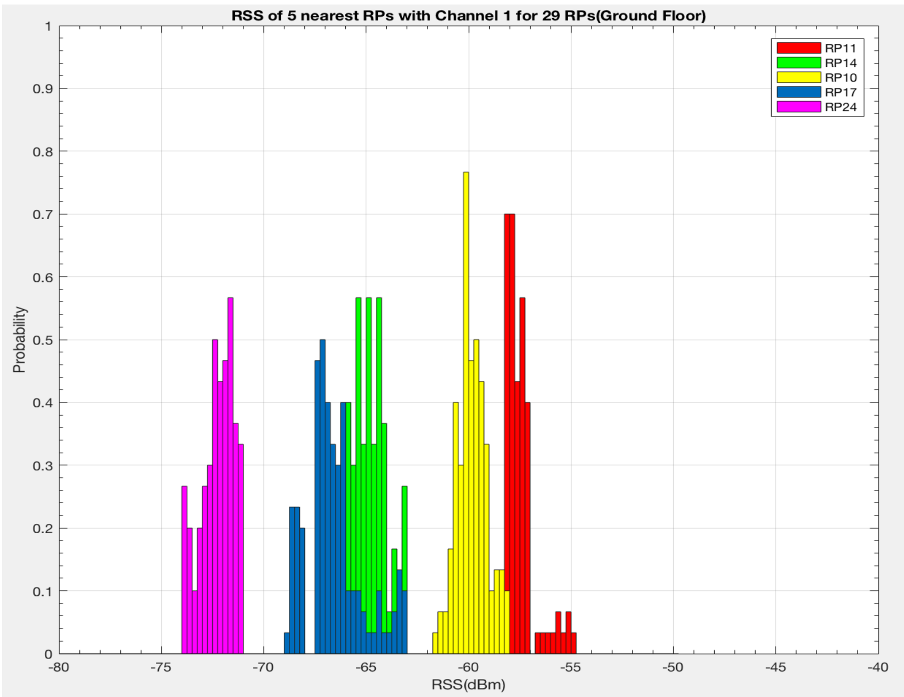

Figure 3.11a. RSS of 5 RPs within small region with channel 1 for 29 RPs in Ground Floor

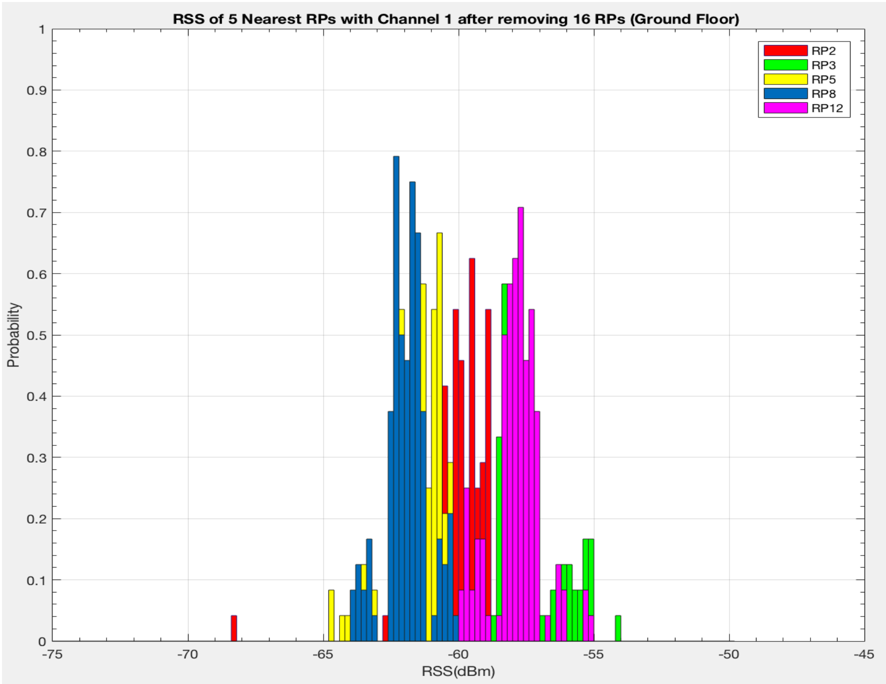

Figure 3.11b. RSS of 5 RPs within small region with channel 1 after removing 16 RPs in Ground Floor

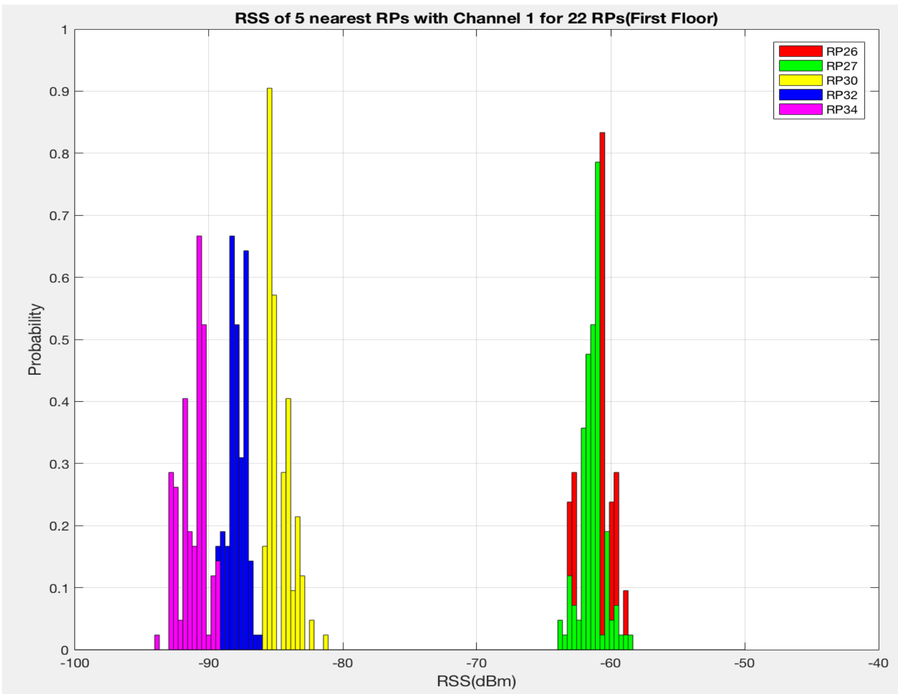

Figure 3.11c. RSS of 5 RPs within small region with channel 1 for 22 RPs in First Floor

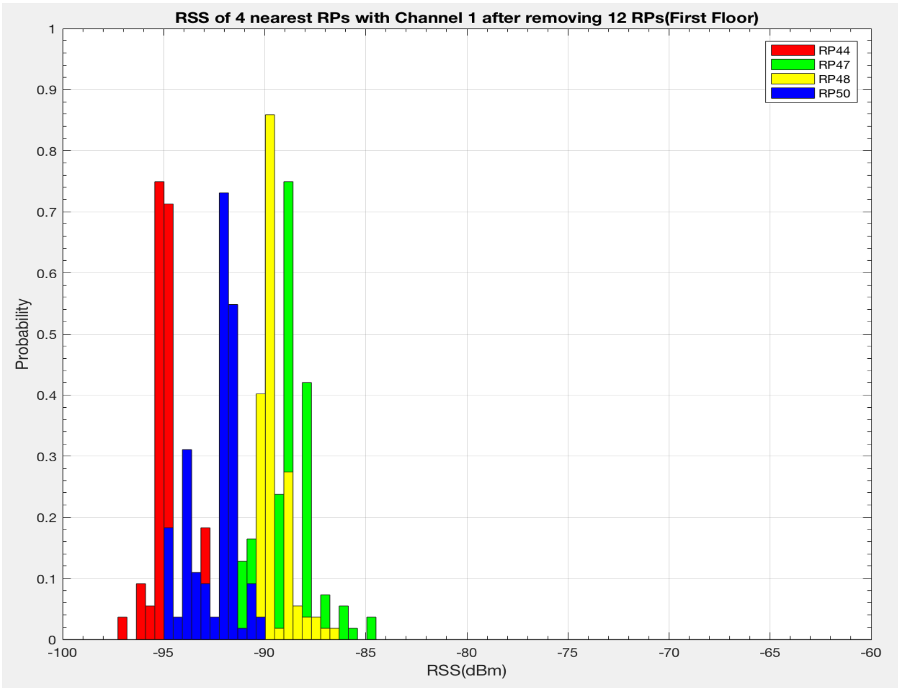

Figure 3.11d. RSS of 4 RPs within small region with channel 1 after removing 12 RPs in First Floor

3.4 Comparison between AM and FM fingerprinting

To compare the precision of our experiment, we highlighted the comparison between AM and FM signal. The FM experiment was conducted by Moghtadaiee [13]. Here, we look at FM's accuracy compare with the accuracy of AM. In brief, the FM experiment was conducted in the same University but in a different location which was the 4th floor of former Electrical Engineering Building. This site was not available for the AM tests. The total size of the site was 23m by 11m, and it was office environment consisting of 150 RPs with 28 TPs. The experiment used a total of 17 FM radio broadcast channels in the band from 88MHz to 108MHz. This section only focuses on accuracy comparison between AM and FM for the deterministic method and the contrast is divided into two categories based on the Ground floor and the First floor. The evaluation of comparison is performed based on MDE and K values for both AM and FM shown in Figure 3.12. The comparison in Figure 3.10 for the KNN method on the ground floor shows that the lowest MDE of 3.089m for FM with KNN method is achieved when K=6 whereas the AM method performed the best at K=1 as described in the previous section. The variation of MDE according to K values are not very significant for FM method, but the AM results show a sharp increase of MDE for values K=5 to K=10. Though it is seen that variation of K values and the MDE for AM and FM are different, the minimum MDEs for AM and FM are very close where AM attained 2.76m at K=1 and FM has 2.96m at K=6. The accuracy of AM positioning wins over the FM in this comparison; however, the FM experiment was performed in an entirely different experimental site and the result of positioning also depend on environmental effects such as walls, structure, and contents of the building.

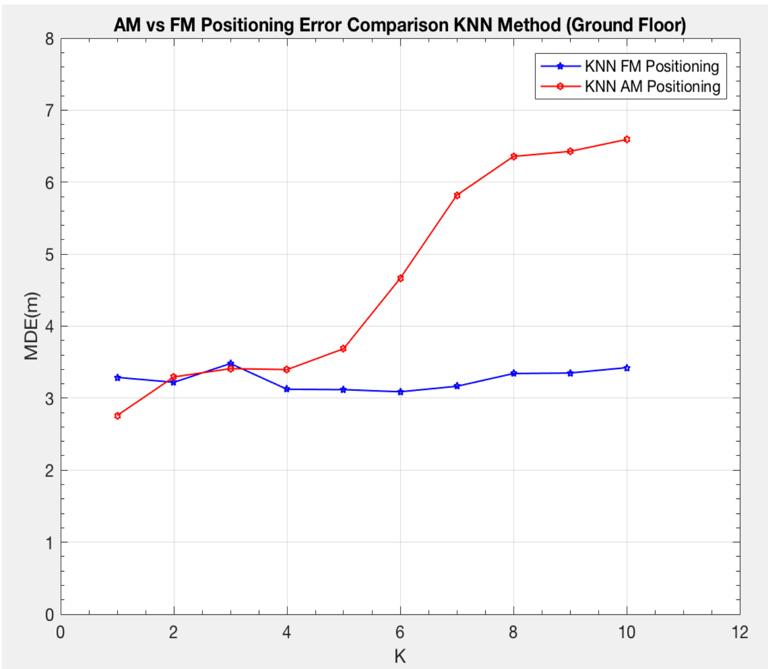

Figure 3.12. AM vs FM Positioning error comparison for KNN method in ground floor

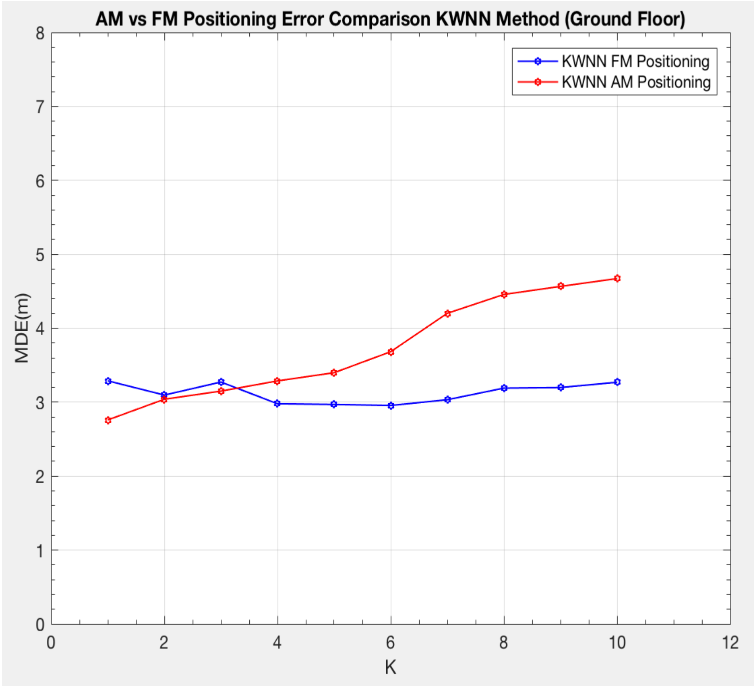

Figure 3.13 AM vs FM Positioning error comparison for KWNN method in Ground floor

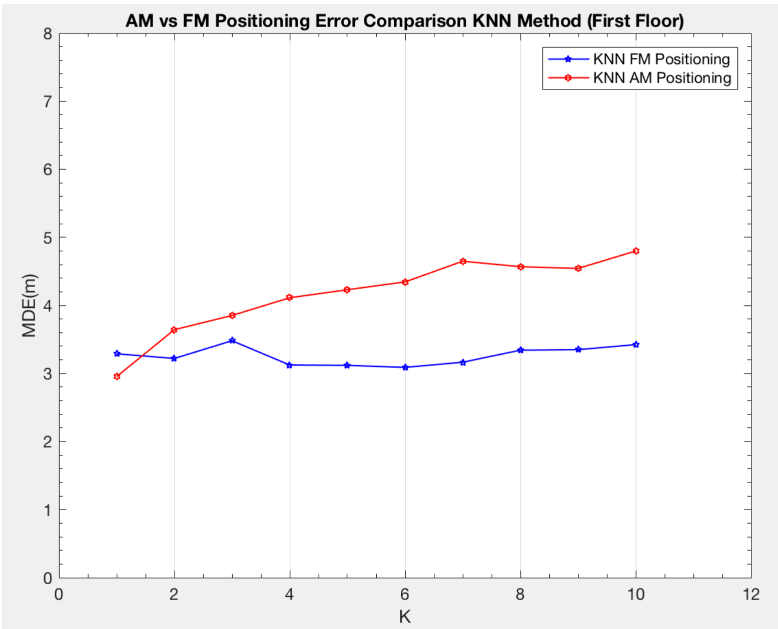

Figure 3.14 AM vs FM Positioning error comparison for KNN method in First floor

Now, Figure 3.13 shows the KWNN method for AM and FM positioning - MDE for KWNN looks very similar to the KNN method shown in Figure 3.12. However, there is a small variation between KNN and KWNN seen through the comparison analysis. On the contrary, the MDE of KWNN for AM positioning at the ground floor shown in Figure 3.13 shows less error from K= 5 in comparison to the KNN method. Though there is little rise at K=8 (see Figure 3.13) for FM signal, the overall MDE looks very consistent with the lowest MDE of 2.96m at K=6. Figure 3.14 and Figure 3.15 show the comparison for KNN and KWNN methods on the first floor. Considering the KNN method, there is no change for FM as the experiment was taken only on one floor. However, the AM shows lowest MDE of nearly 3m at K=1 with an increasing trend which reached to maximum MDE of 4.799m at K=10 whereas the FM has best MDE of 3.089m at K=6. The worst-case scenario for FM positioning is for MDE of 3.48m at K=3. For KWNN in Figure 3.15, the AM positioning behaves interestingly as the lowest MDE started at K=1 with MDE of 2.954m then increased up to K=4. Then the MDE of AM signal has slightly increasing trend which behaved parallel to FM with bit higher error and ended up to the maximum MDE of 4.098 m at K=7. Although, having a large error difference between AM and FM for KWNN in first floor, the overall MDE lines for both positioning look very consistent in compare to previous figures.

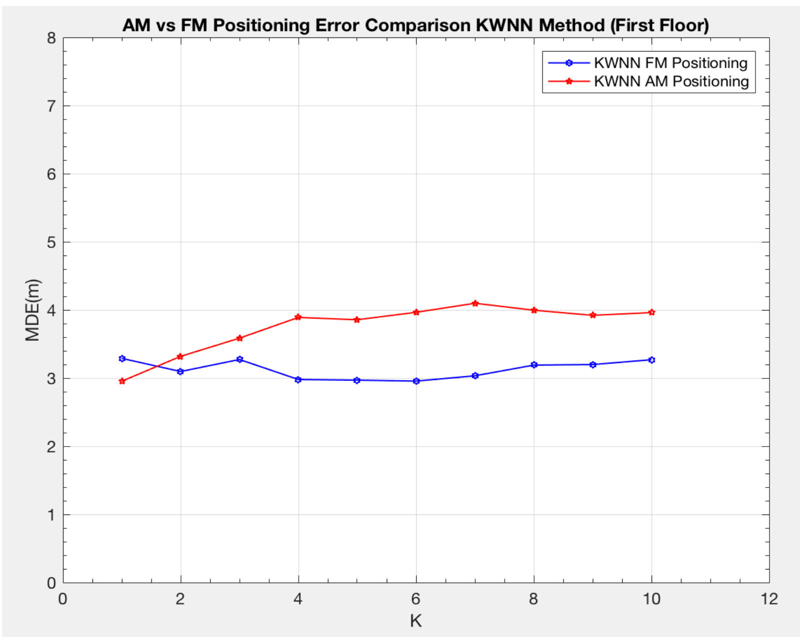

Figure 3.15 AM vs FM Positioning error comparison for KWNN method in First floor

However, there are few factors we need to consider before drawing conclusion of which one works better- AM or FM? From the signal property perspective, FM is always better because of its less susceptibility to interference like barriers within the building and the building structure. However, AM fingerprinting worked fine with lowest MDE of 2.76m in this instance, though this primary result does not mean AM beats FM consistently. The results after removing the number of RPs for AM fingerprinting showed that the initial removal of the first sets of 6 RPs on both floors lowers the performance. However, the winning situation of NN with the full number of RPs was unexpected and unusual which was investigated later via the RSS variation of RPs within a selected small region of both floors. Then, removing more RPs from both levels showed that the KNN and KWNN performed way better than NN, which is very conventional. The significant RSS variation among the RPs (more than 10dBm in the Ground floor) shown in histograms also let us think that the vast difference of RSS (around 20dBm in the First floor) among the RPs close to each other within a small region causing the issue of NN's best performance primarily. Therefore, we can predict that the reason of significant change for RSS is due to multipath, building structure and other barriers within the rooms. If the first sets of removed RPs of both floors were rearranged or localized differently, the AM results would have been different where KWNN might have performed better than NN. Moreover, some factors such as experimental site, number of RPs, the arrangement or planning of RPs and TPs, Data Acquisition time and device, number of samples need to be same to compare the performance between AM and FM fingerprinting equally. As most of the requirements were completely different for two experiments, therefore, it won't be rational to make one signal winner over another only based on experimental data.

Chapter 4

Conclusion and Future Work

4.1 Conclusion of the Research

Not all positioning technology can perform well in every environment. In most cases, GPS has been a worldwide recognized and commonly used technology, but it also has functioning limitations in the indoor environment and urban areas. Through the utilization of signals of opportunity in conjunction with GPS can overcome the navigation difficulties in such areas. To implement SoOp for navigation and to avoid issues related to NLOS and multipath, the fingerprinting method for indoor localization has been investigated in this research. Also, this study was performed at a minimal cost without compromising the accuracy and performance of the outcome. This research has been conducted for the very first time for indoor navigation utilizing AM signals for indoor positioning. The study had the objective of addressing performance issues such as limitations of current fingerprinting techniques and the improvement of accuracy by implementing AM signal for indoor positioning, which has been focussed on and discussed. This dissertation used the deterministic approach for positioning measurement. The data analysis of the results was carried out based on the three algorithms such as NN, KNN, and KWNN which are demonstrated against three criteria such as mean distance error (MDE), K values and number of channels. Further investigation also showed the impact of frequency diversity and spatial diversity on the positioning accuracy and performance. Also, we carried out an analysis by varying number of RPs which allowed us to observe how the MDE for different algorithms changes according to the removing RPs from various parts of two floors. The obtained results of the experiment show that the AM signal for fingerprinting gave an accuracy of 2.8m and 3.0m on the ground floor and first floor respectively. However, further investigation of NN's unconventional best performance was achieved via RSS analysis of RPs within a small region of both levels. The results highlighted that the variation of RSS from RP to RP could have a significant impact on localization accuracy. Finally, the comparison between AM and FM signals has been highlighted by comparing their results obtained from NN, KNN and KWNN methods. Despite the impact of environment and the location of the experimental site for FM and AM experiments, the result comparison highlights that the accuracy and the performance of AM and FM signals for fingerprints are relatively similar. The AM positioning attained a slightly higher accuracy of 2.76m on the ground floor and 2.954 on the first floor, on the contrary, FM had 2.96m.

4.2 Future Work:

The following work can be conducted in the future based on our results and analysis:

1. As our current study has a limitation of the number of measurements and number of samples, therefore, the probabilistic approach was not good enough to carry the accuracy test. Thus, the number of samples and enhancement of the quantity of RP and TP in the future would widen the scope of increasing the accuracy for AM signal positioning.

2. the past study for FM fingerprinting carried out with the hybrid method with the conjunction of Wi-Fi fingerprints which showed the better efficiency of the hybrid method. So, we also plan to integrate Wi-Fi with AM signal.

3. According to our observation, the impact of frequency diversity can increase or decrease the accuracy of positioning; therefore, there is scope left to investigate the frequency diversity for the hybrid method with AM and FM or AM and Wi-Fi for indoor navigation.

4. We only tested Euclidean distance for measurements; however, there is scope to use Manhattan, Chebyshev, Sorensen, Canberra, Cosine and Hellinger Distance to verify and compare the accuracy of positioning.

5. The size of the AM receiver is an issue as this thesis utilized Tektronix spectrum analyser due it's high accuracy and reliability of it's data acquisition capability. However, it is not very practical to use handheld spectrum analyser for navigation purpose in real life situation. Therefore, embedding AM radio receiver either with mobile phone or miniaturizing of AM receiver with navigation capability is essential for practical navigation purpose. Due to long wavelength of AM signal it is essential to have long antenna with the AM receiver which is very complicated to embed with today's latest mobile phones. That's why another possibility might be the use of mobile phone's earphone cable as a wearable antenna for the embedded AM radio receiver.

However, a further study on designing a separate AM receiver only for the navigation purpose would be new field of our research.

6. Last but not the least, as there are some other techniques such as Neural Network, Support Vector Machine and Smallest Vertex Polygon available, therefore, we have a chance to implement these methods to compare the accuracy for the deterministic and probabilistic approach.

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